DIVISION S-5—PEDOLOGY

Differentiating Soil Types Using Electromagnetic Conductivity and Crop Yield Maps

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ABSTRACT

Variable rate technology enables management of individual soil types within fields. However, correct classification of soil types for mid-Atlantic coastal plain soils are currently impractically expensive using an Order I Soil Survey, yet variable rate fertilizer application based on soil type can be highly effective. The objectives of this study were to determine if apparent electromagnetic conductivity (EC_a) alone or combined with previous year crop yields using global positioning system technology can provide a useful alternative to detailed soil mapping. The site contained alluvial soils ranging from Bojac 1 and 2 (coarse-loamy, mixed, thermic, Hapludults) to Wickham 3 and 4 (fine-loamy, mixed, thermic, Ultic Hapludalfs). The two fields totaled approximately 24 ha. A statistical nonparametric classification method, called recursive binary classification trees, was used to determine how well soil types could be classified. Electromagnetic conductivity readings and crop yields were positively correlated. Broad patterns in the relationship between soil types and EC_a readings and crop yields existed for all crop combinations considered. Lower EC_a readings and crop yields corresponded to the Bojac soils, while higher EC_a readings and crop yields were categorized as Wickham soils. Electromagnetic induction alone correctly classified the soils into broad categories of Bojac or Wickham with over 85% accuracy. When EC_a was combined with crop yield data, correct classification rose to over 90%. More precise classification into Bojac 1, Bojac 2, and Wickham soils yielded slightly lower correct classifications ranging from 62.6 to 81.2% for EC_a alone, and 80.3 to 91.5% when combined with various crop yields.

Variable rate fertilization strategies based on soil type have potential to lower fertilizer inputs and increase profits in the mid-Atlantic coastal plain. Conventionally, fertilizer application to a farm-field is based upon the most productive soil in that field. Consequently, low productivity areas of the field may be over fertilized. The use of variable-rate fertilizer applicators equipped with global positioning systems (GPS) and georeferenced soil maps enables nutrient applications that better match crop requirements on various soils within a field. Applying fertilizer based on yield potentials associated with specific soil factors such as water-holding capacity, optimizes yield response to fertilizer and reduces potential loss to ground and surface waters.

Soil specific fertilization strategies require accurate soil maps. Robert (1993) discusses the viability and cost-effectiveness of a number of options available for creating these maps. In the mid-Atlantic coastal plain, soil property changes within fields are often abrupt because of the alluvial nature of the soils. Fields typically contain two or more soil types. These soil types vary in productivity potential because of differences in soil properties, particularly those properties that influence soil water-holding capacity, such as clay content. County soil surveys often fall short of the spatial accuracy required to realize the benefits of variable rate technology, however these surveys provide excellent information regarding the soil types that may be encountered in the field. Order 1 soil surveys (Soil Survey Staff, 1993) provide accurate soil maps, however they are generally expensive to make, or difficult to obtain (Robert, 1993).

Variable rate fertilizer applications in the mid-Atlantic region are generally based on soil test values for P, K, and lime applications, and soil yield potential for N fertilizers. Soil sampling strategies for P, K, and lime applications range from grid sampling to management zone sampling strategies that are based on soil types. These sampling techniques may then be used to determine fertilizer application rates ranging from one rate to a different rate for each sampled location. Recent work has shown that in cases with relatively little systematic variation across a field, a *composite-by-soil* sampling approach can provide effective fertilizer recommendations with lower sample numbers (Anderson-Cook et al., 1999). The composite-by-soil approach involves collecting multiple samples from each known soil type and using a composite sample by soil type as an aggregate measure of soil fertility and corresponding fertilizer recommendation for each soil type within a field. The composite by soil type sampling approach has reduced sampling and analytical costs, compared with grid sampling strategies, but accurate soil maps are required to employ this strategy (Anderson-Cook, 1999).

In this paper we consider the use of an electromagnetic induction meter, EM38 (Geonics Limited[1], Mississauga, ON, Canada) to develop soil maps for use in variable rate fertilizer application. McNeill (1986) has described principles of operation for the EM38. Apparent electromagnetic conductivity uses electromagnetic

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[1] Mention of trade names is solely to provide information for the reader and does not constitute endorsement of the instrument or product by Virginia Polytechnic Institute and State University, Colorado State University or USDA.

Abbreviations: EC_a, apparent electromagnetic Conductivity; GPS, global positioning system.

energy to measure the apparent conductivity of a column of soil material to a specific observational depth (0.75–1.5 m). Electromagnetic conductivity measurements have been used as a surrogate measure for soil properties such as salinity, soil moisture content, topsoil depth, and clay content (Sudduth et al., 2001). Scanlon et al. (1999) showed that EM38 measurements correlate well with clay content and soil moisture content, two properties that can vary between soil types and influence crop yield potential of soils. Soil salinity as a factor influencing EM38 measurements is generally minimal in the mid-Atlantic coastal plain because of regular leaching events in this high rainfall region (>1000 mm annually). Zalasiewica et al. (1985) used ground conductivity to improve geological mapping, and Rhoades (1981) discussed predicting soil electrical conductivity from soil type. In addition, Rhoades et al. (1989) produced a model describing the relationship between bulk soil electrical conductivity and electrical conductivity of soil water. Doolittle et al. (1995) evaluated the use of EC_a measurements with GPS to conduct reconnaissance soil mapping. Thus, EM38 measurements have potential for mapping soil zones of differing productivity potential for variable rate fertilization strategies.

In this research, we compare the effectiveness of the EC_a readings to correctly differentiate soil types relative to an Order I Soil Survey (Soil Survey Staff, 1993). We also investigate combining EC_a readings with previous crop yield maps obtained using a combine yield monitor and GPS technology that may further improve soil categorization for use in precision agriculture.

THEORY

The goal of utilizing the EC_a meter and GPS is to provide a mechanism for accurately predicting soil type in a time and cost-effective manner. The EM38 induction meter has been used to measure topsoil depth in claypan soils in Missouri (Doolittle et al., 1994) as well as the depths of sand deposition following flooding (Kitchen et al., 1996). Jaynes et al. (1995) and Sudduth et al. (1999) investigated the relationship between yields and topsoil depth as estimated by electromagnetic induction methods. The Iowa study of Jaynes et al. (1995) showed yields of corn (*Zea mays* L.) and soybean (*Glycine Max.* L.) were correlated with electromagnetic measurements, but correlations were not consistent from year to year. The authors indicated that the lack of consistency of the correlations was due to variable spring moisture conditions associated with poorly drained soil conditions. Sudduth et al. (1999) reported that corn grain yields were correlated to EM38 measurements ($r = 0.93$), especially in years where water availability was a limiting factor.

In this study the results of an Order I Soil Survey were used to define soil type known to require different management strategies to optimize crop yields. We sought to develop a model to compare the EC_a readings to the Order I Soil Survey. Statistical methods were utilized to determine how precisely the EC_a meter responses could classify known soil types. Since little was known initially about the relationship between electromagnetic induction readings and soil type, a nonparametric approach for modeling the relationship with little imposed structure was taken.

Classification trees are similar to regression modeling, in that the original data suggests an estimated model from which prediction is possible for new values of the explanatory variables. However, in this case the response is not a continuous measurement, but rather a category. The classification trees are an automated statistical tool for partitioning the ranges of explanatory variables, $X_1, \cdots, X_k$, into a unique classification of the response, in this case soil type. Based on the classification suggested by the tree, each combination of values for the variables, $x_1, \cdots, x_k$, suggests a single category for the response. As with a regression model, the response is required for the model fitting stage to determine the nature of the relationship between response and explanatory variables. When the model is used for predictions, only the explanatory variables, $x_1, \cdots, x_k$, are required.

The tree is constructed from the observed data with a recursive binary partitioning algorithm (Breiman, 1984; Clark and Pregibon, 1992). The algorithm works to repeatedly split the data into advantageous groupings to optimize the prediction ability of the explanatory variables to describe the response. At each stage of the algorithm, the split of the ranges of the $X_1, \cdots, X_k$'s into an additional classification region is based on maximizing the improvement in the correct classification rate for the response. To ease the computational demands of tree construction and to make the interpretation of results more straightforward, each split of the data involves only a single true-false decision involving a single variable. Splitting the ranges of the explanatory variables continues in the algorithm until subsequent splits fail to yield sufficient improvement in the model to justify continuing.

The result of the classification tree is a series of decisions, displayed in an inverted tree. Figure 1a gives a sample tree using two explanatory variables, X_1 and X_2. Starting at the top of the figure or root, we determine whether to go left for a true decision or right for a false decision at each branch, until we have reached the bottom leaves, which tell us the classification for each particular combination of values for X_1 and X_2. For example, if $x_1 = 25$ and $x_2 = 22$, we would predict the response as Category 1, while if $x_1 = 33$ and $x_2 = 14$, we would predict Category 2.

An alternate summary of the tree is given in Fig. 1b where the ranges of X_1 and X_2 values observed in the data are partitioned into regions. Note that each horizontal or vertical line corresponds to a single decision involving either X_1 or X_2, respectively in Fig. 1a. To use this summary to predict, we would locate a combination, say $x_1 = 25$ and $x_2 = 22$, on the plot and then predict the category based on the label for that region; that is, Category 1.

The major advantage of using classification trees to categorize the responses is the flexibility of this nonparametric method to accommodate many different functional forms of a relationship and avoid imposing a prespecified structure on the data. Unlike regression (for continuous responses) or logistic regression (for categorical responses), no continuity, smoothness, or other global structure for the relationship is assumed. Additionally, the method is easily implemented using S-Plus software by Mathsoft, (S-Plus, 2000), with existing functions to construct and display the trees.

MATERIALS AND METHODS

The soils of the experimental site (Fig. 2) in the Virginia coastal plain were determined by an Order 1 soil survey (Nicholson et al., 1998) using the methods of the National Cooperative Soil Survey soil survey manual (Soil Survey Staff, 1993). The site contained alluvial soils ranging in productivity. The Bojac 1 soil has higher productivity than the Bojac 2 soil, and the Wickham 3 and 4 being the most productive soils in the study. Soil profile characteristics are given in Table 1. Ranges

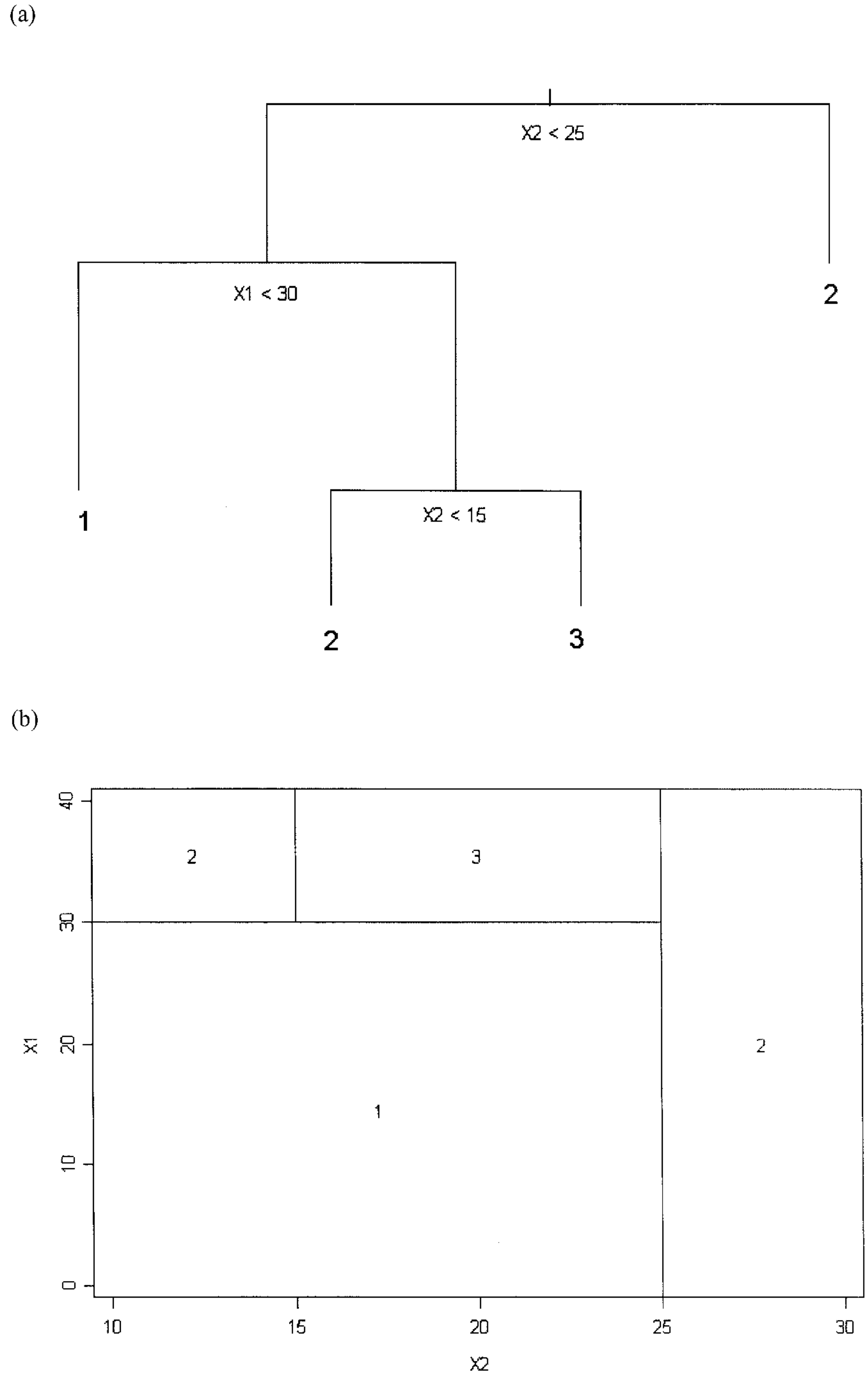

Fig. 1. Summaries of classification tree categorization. (a) Inverted "tree" structure for classifying observations with two explanatory variables, X1 and X2. (b) Partition of the observation space of X1 and X2 into classification regions. Values of X1 and X2 are hypothetical.

in productivity and fertilizer needs are associated with available water-holding capacity and soil texture (Simpson et al., 1993). The total study area is approximately 24 ha.

Electromagnetic measurements were made using an EM38 induction meter (Geonics Limited, ON, Canada) on 2 Dec. 1998. McNeill (1980a) described the principles underlying the use of electromagnetic techniques to detect differences in soil properties. The EM38 instrument resembles a carpenter's level, is approximately 1 m long, and includes calibration controls and a digital readout of EC_a. All EC_a measurements reported in this study were standardized to an equivalent electrical conductivity at 25 °C as conductivity changes 2.2% °C^{-1}. (McNeill, 1980b). The instrument was operated in this study in the horizontal mode, which provides an effective measurement depth of approximately 0.75 m (McNeill, 1992). The EC_a meter readings were taken on a grid at approximate 30.4-m intervals along 21 strips each 18.5 m apart. Global positioning system receivers coupled to a microcomputer recorded the location of the measurements as well as the measured and temperature-corrected apparent conductivity. The 21 strips are part of a larger study involving multiple crop rotations. Hence, measurements were divided into the four distinct crops (corn, barley [*Hordeum vulgare* L.], wheat [*Triticum aestivum* L.], and soybean). The Order I Soil Survey results were matched with the EC_a read-

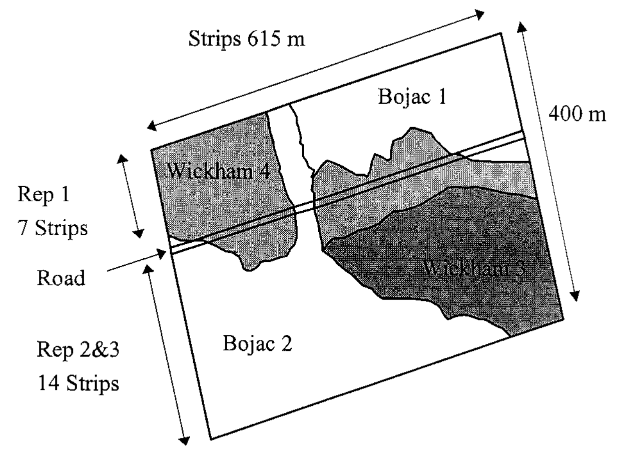

Fig. 2. Order 1 soil survey map of the experimental site in the northern Virginia coastal Plain (Nicholson et al., 1998).

ings using the GPS locations. Thus the classification of each rectangle area in the output graphs of the cluster analysis to a soil type was determined by examining the data within that region and selecting the soil type which comprised the majority of observations using the associated GPS location and Order 1 soil survey data. Since the Wickham 3 and 4 soil types did not require separate management strategies for fertilizer application because they have similar water-holding capacities, they were combined into a single type. Additionally, the task of trying to separate the Bojac and Wickham soils using EC_a and crop yields was also considered to distinguish the soil types into broader, easily discernable categories.

Before any analyses were considered, locations at or within 10 m of the boundary between soil types were removed from the data set. As these soil measurements would likely be a graduation between the soil types being studied, they could not be defined as a specific soil type. Thus we were unable to relate EC_a for these specific points to a reference soil type from the Order 1 soil survey. Therefore, of the initial 524 measurements, only 472 were considered.

Yields for a variety of crops during 1998-1999 were determined by harvesting with a John Deere 9610 combine (Deere and Company, Moline, IL) equipped with the Greenstar yield monitor (Deere and Company, Moline, IL) and GPS receiver with differential correction. Yields and the associated locations were recorded at 1-s intervals by translating flow and area harvested into an instantaneous yield measure. For each crop, a global adjustment for standard payable moisture was applied. Since crop yield and EC_a data were to be considered together as possible explanatory variables in a model to predict soil type, GPS locations associated with both variables were used to combine the data. Both the nearest crop yield measurements for a given crop and the average of the three nearest yields to the measurement locations of EC_a were considered. Five separate analyses were considered using the different crop rotations. Results are presented for 1998 and 1999 full-season corn, 1999 barley, 1999 wheat, and 1999 double-crop soybeans.

RESULTS AND DISCUSSION

Initial examination of the data showed differences in EC_a values for the broad classes of Bojac and Wickham soils (Table 2). The Bojac soils have lower conductivity associated with lower moisture retention than the Wickham soils. Differences within the Bojac 1 and 2, and the Wickham 3 and 4 soils are less, as would be expected, because surface soil textures are similar (Table 1).

Table 1. Soil horizon, depth, color, and texture for the four soils at the experiment site in the northern Virginia coastal plain.

Soil	Horizon	Depth	Munsell color	Texture
		cm		
Bojac 1	Ap	0–33	10YR 3/4	Loamy sand
	Bt1	33–81	75YR 4/6	Sandy loam
	Bt2	81–142	5YR 4/6	Sandy clay loam
	BC	142–165	7YR 5/8	Loamy sand
	C	165–203	75YR 6/8	Loamy sand
Bojac 2	Ap	0–30	75YR 3/4	Loamy sand
	Bt1	30–104	75YR 4/6	Sandy loam
	Bt2	104–178	75YR 4/6	Loamy sand
	C	178–203	75YR 5/6	Loamy sand
Wickham 3	Ap	0–25	75YR 4/4	Sandy loam
	Bt1	225–64	5YR 4/6	Clay loam
	Bt2	64–89	5YR 4/6	Loam
	Bt3	89–140	75YR 4/6	Sandy clay loam
	C	140–203	75YR 4/6	Loamy fine sand
Wickham 4	Ap	0–33	75YR 3/3	Sandy loam
	Bt1	33–61	75YR 4/6	Sandy clay loam
	Bt2	61–89	75YR 4/6	Clay loam
	Bt3	89–140	75YR 4/6	Clay loam
	Bt4	140–178	5YR 4/6	Loam
	C	178–203	75YR 4/6	Sandy loam

Division of the data into crops separated the 472 observations into four crop groups depending on which crop yield was considered. Therefore some of the EC_a observations were used more than once in association with different crops in a rotation. Comparison of EC_a measurements to nearest crop yield measurements for a given crop and the average of the three nearest yields resulted in classification tree models that were virtually identical for both approaches. The data presented here related EC_a measurements to nearest crop yield measurement.

The effectiveness of classification trees using the EC_a data and crop yields to separate the broad classes of Bojac and Wickham soils are summarized in Table 3. The percentage of correct classification reported indicates successful soil type categorization using the classification tree approach and how well gross differences between the soil types can be identified using EC_a and crop yields. For each of the crop systems, either EC_a or crop yields alone separate the Bojac and Wickham soils. The EC_a results are expected because the means of the EC_a measurements within the two soil series are quite different relative to their standard deviations (Table 2). It should be noted that there is considerable consistency in the predictive power of EC_a values across the different crops. For all of the crops, between 85 and 95% of the data are correctly classified using only EC_a measurements. However, in four of the five crops considered, combining EC_a with crop yields gives improvement in

Table 2. Electromagnetic induction measurements by soil type. Data were temperature corrected to 25°C.

	Soil Type			
	Bojac 1	Bojac 2	Wickham 3	Wickham 4
No. observations	80	180	113	99
Average, mS m^{-1}	2.60	2.84	5.29	4.21
S.D., mS m^{-1}	0.94	0.97	1.23	0.82
Average, mS m^{-1}	2.77		4.79	
S.D., mS m^{-1}	0.96		1.19	

Table 3. Percentage correct classification rate of classification trees for Bojac versus Wickham soil types using apparent electromagnetic conductivity (EC_a) and crop yields alone and combined.

Crop	Number of observations	EC_a Alone	Crop yield alone	EC_a & crop yield
		% correctly classified		
No-till full-season corn 1998	129	85.3	88.4	91.5
No-till full-season corn 1999	197	91.4	88.8	96.4
No-till barley 1999	67	95.5	86.6	95.5
No-till wheat 1999	211	87.2	83.0	93.4
No-till double-crop soybean 1999	259	87.6	70.0	90.3

classification success (Table 3). Yield data generally improve the classification over EC_a data alone because crop yields tend to reflect soil moisture holding capacities for these coastal plain soils. The exception to improvement in classification success using yield data was the Barley misclassification rate, which remains the same when using EC_a alone or in combination with crop yield data. A misclassification rate below 10% for all of the crops suggests the effectiveness of this approach for distinguishing between Bojac and Wickham soils, regardless of the crop being grown.

Figures 3 and 4 show the partitioning plot for the classification trees for 1999 no-till full-season corn and 1999 no-till wheat. The *x*-axis shows the EC_a values, while the *y*-axis gives the crop yield for the corresponding GPS location. The points on the plot are the data collection sites corresponding to a particular combination of EC_a with corresponding crop yield. The relatively high variability of the yields within soil types is a reflection of the 1-s interval readings of the yield monitor being translated into a kilogram per hectare summary. The rectangles form boundary lines around the different soil type classifications. The shaded region corresponds to Wickham soil, while the unshaded region predicts the Bojac soil. Lines inside each region indicate a separate decision in the classification tree, however, we are primarily interested in how the broad patterns defined by different combinations of EC_a readings and crop yields predict soil types.

The EC_a and yield measurements are significantly and positively correlated (ranging from 0.16 for wheat to 0.54 for corn). This positive correlation is related to the EC_a relationship with clay content and soil water content at the time of measurement and crop yields relationship with clay content and soil water holding capacity. The values of the EC_a increase with increasing clay content and soil moisture. At the time of EC_a measurement in December the soil water content would have closely reflected the differences in water-holding capacity because of a recharge of the soil profile by rainfall. For this reason the data is not uniformly spread throughout the ranges of the explanatory variables, as seen by the relative lack of observations in the top-left and bottom-right corners of the plots. The combination of low EC_a and low crop yield is consistently categorized as Bojac soil, while observed data associated with higher EC_a

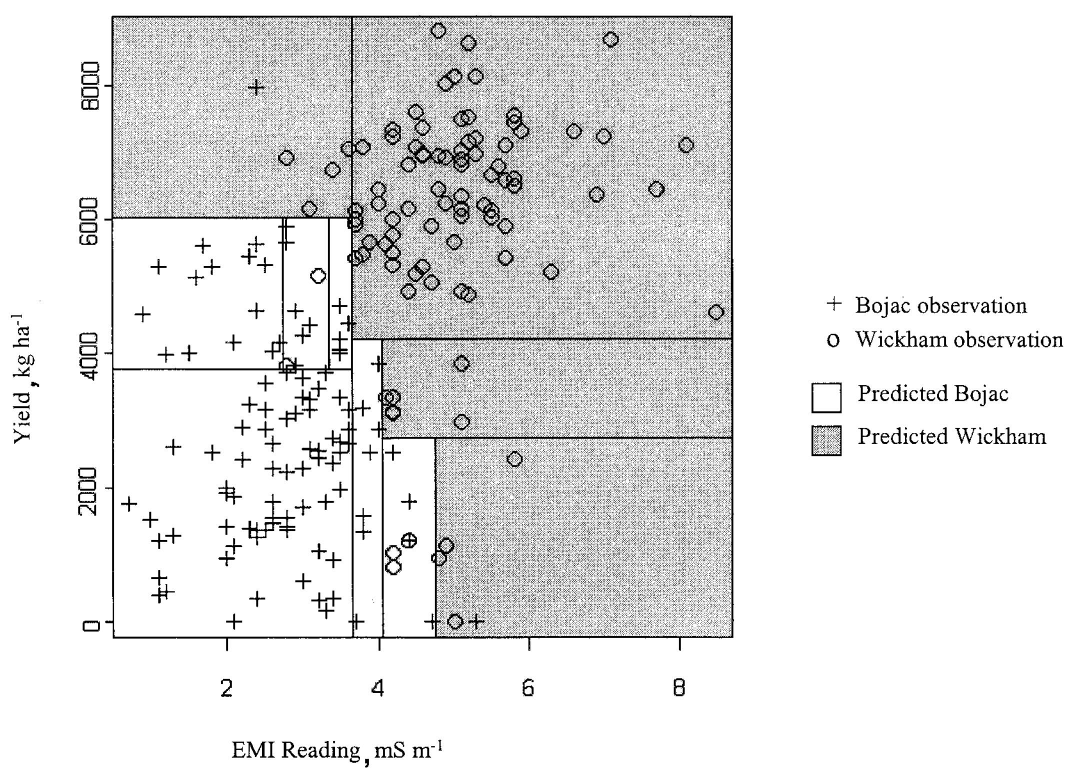

Fig. 3. Classification partition for Bojac versus Wickham soil types using apparent electromagnetic conductivity (EC_a) and 1999 no-till full-season corn yields. The classification of each rectangle is determined by whichever soil type comprises the majority of observations.

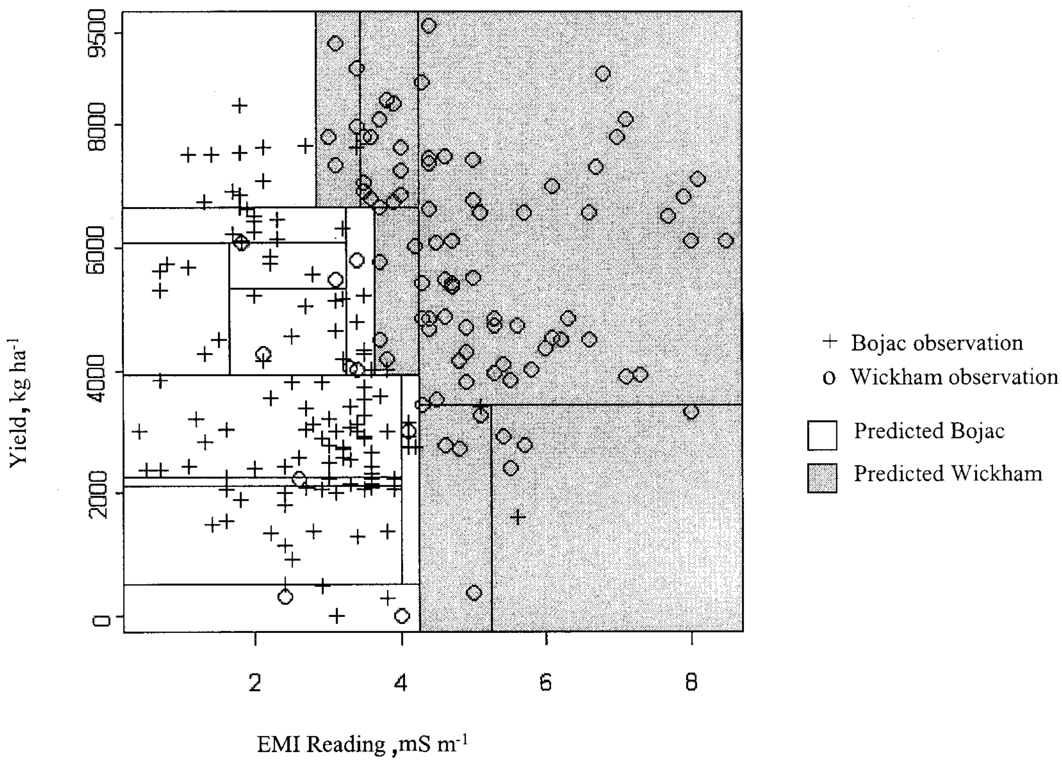

Fig. 4. Classification partition for Bojac versus Wickham soil types using apparent electromagnetic conductivity (EC_a) and 1999 no-till wheat yields The classification of each rectangle is determined by whichever soil type comprises the majority of observations.

and crop yield is categorized as Wickham. This was the general pattern for the separation of Bojac and Wickham soils for all crops evaluated.

Because of the positive correlation between EC_a readings and crop yields, high EC_a reading corresponding to low yields, or a low EC_a reading corresponding to high crop yields were rare. For these combinations, there are some small differences in the classifications for the 1999 corn data (Fig. 3) and the 1999 wheat data (Fig. 4).

The number of branches or decisions in the trees, denoted by the number of horizontal and vertical lines on the partitioning plot, indicate the complexity of the relationship between the explanatory variables and the soil type response. Since the classification tree algorithm cannot assign diagonal lines to separate data, it must use multiple horizontal and vertical lines for this purpose. The classification tree approach is strongly empirically based and does not force global structure on the relationship between explanatory variables and the response. The fact that even with this unrestricted nonparametric method, adjoining regions of EC_a and crop yield are consistently categorized as one soil type, indicates that a true relationship has been identified.

The 1999 barley classification tree (data not shown) separates the soils with one vertical line, indicating that only EC_a is important for soil type delineation for this crop. In this way the classification tree can be considered a variable selection technique as well, since it chooses at each stage not to include the crop yields as an informative variable for separating the soil types. Since crop yields are not used in the barley analysis, we have the same correct classification rate for both EC_a alone and EC_a with crop yield trees (as shown in Table 3).

Table 4 shows how the soil types are classified using EC_a and crop yield for both the 1998 and 1999 no-till full-season corn yields. Comparison of results between the corn years shows the consistency of the results from year to year, and in different locations in the total study area. In both years, over 90% of soil types are correctly classified, with the Bojac soils having a smaller misclassification rate. To obtain the total correct classification rate summarized in Table 3, a weighted average of the correct classification rates based on the relative areas of the soil types is taken for each soil.

Given the ability of the statistical method to differentiate between the two major soil groups, we investigated

Table 4. Classification rates for individual soil types using electromagnetic induction and 1998–1999 no till full-season corn yields for Bojac versus Wickham soil types.

	1998 Corn			1999 Corn		
		Predicted soil type			Predicted soil type	
True soil type	Number of observations	Bojac	Wickham	Number of observations	Bojac	Wickham
		%			%	
Bojac	74	93.2	6.8	105	98.1	1.9
Wickham	55	10.9	89.1	92	5.4	94.6

Table 5. Percentage correct classification rate of classification trees for Bojac 1, Bojac 2, and Wickham (3 and 4) soil types.

Crop	Number of observations	EC_a alone	Crop yield alone	EC_a & crop yield
		% correctly classified		
No-till full-season corn 1998	129	72.1	78.3	85.3
No-till full-season corn 1999	197	81.2	80.2	86.8
No-till barley 1999	67	80.6	74.6	85.1
No-till wheat 1999	211	73.9	81.0	91.5
No-till double-crop soybean 1999	259	62.6	59.1	80.3

separating data further into variants within the Bojac (Bojac 1 and Bojac 2) and Wickham (Wickham 3 and Wickham 4) soils. When attempting to classify the soil types into four groups, Bojac 1, 2 and Wickham 3 and 4, the correct classification rates dropped considerably, as the statistical method was unable to distinguish between the two Wickham soils effectively. This reflects the similarity of the two variants of the Wickham soil. The visually detectable differences between the two variants of Wickham that lead to separate soil classification do not translate into differences in water-holding capacity or yields. This result indicates the differences do not translate to a broad difference in electrical conductivity. In terms of soil mapping for determining soil maps for variable rate fertilization programs, the Wickham soil variants would receive the same fertilizer rate as they are of the same soil productivity class (Simpson et al., 1993). Thus we tried separating the soils based on soil productivity class using the EC_a measurements to predict if the soil type was Bojac 1, Bojac 2, and the Wickham soil units combined. The productivity potential differences between these three soil types are closely related to soil water-holding capacity (Roygard et al., 2002).

Results from the different classification trees are summarized in Table 5. As with the previous separation into just Bojac and Wickham soils, we find that combining EC_a and crop yields improves the separation compared with the use of either of the variables considered alone (Table 5). Except for the soybean data, where an unusual precipitation pattern (170 mm of precipitation in 2 d in a September hurricane) resulted in few yield differences between soils, the combined trees are able to correctly classify over 85% of the observations into the three soil types. Indeed, for the area of the field where the no-till double-crop soybeans were planted in 1999, the EC_a readings alone do not seem to be as effective, as shown by the low correct classification rate of 62.6% for EC_a alone. The reason for this change in pattern is unknown. The 1999 wheat data was the best classifier into the three soil groups with 91.5% being correctly classified, while the corn and barley yields combined with EC_a readings gave correct classification rates approximately 85% (Table 5).

Examining the results for the 1998 and 1999 no-till full-season corn crops, we find similarities between classification patterns for the three soil types. Figures 5 and 6 show the regions specified. The 1998 corn yield and EC_a classification partition shows just three distinct regions for the three soil types (Fig. 5). Given the nonpara-

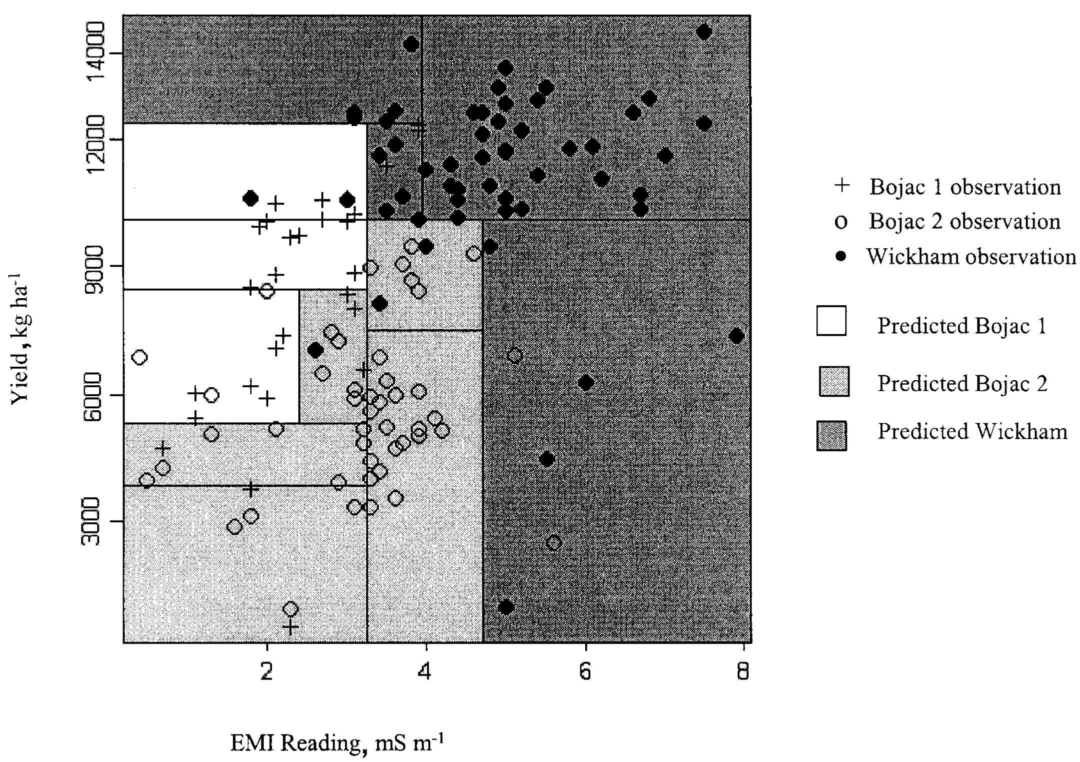

Fig. 5. Classification partition for Bojac 1, 2 versus Wickham soil types using apparent electromagnectic conductivity (EC_a) and 1998 no till full-season corn yields. The classification of each rectangle is determined by whichever soil type comprises the majority of observations.

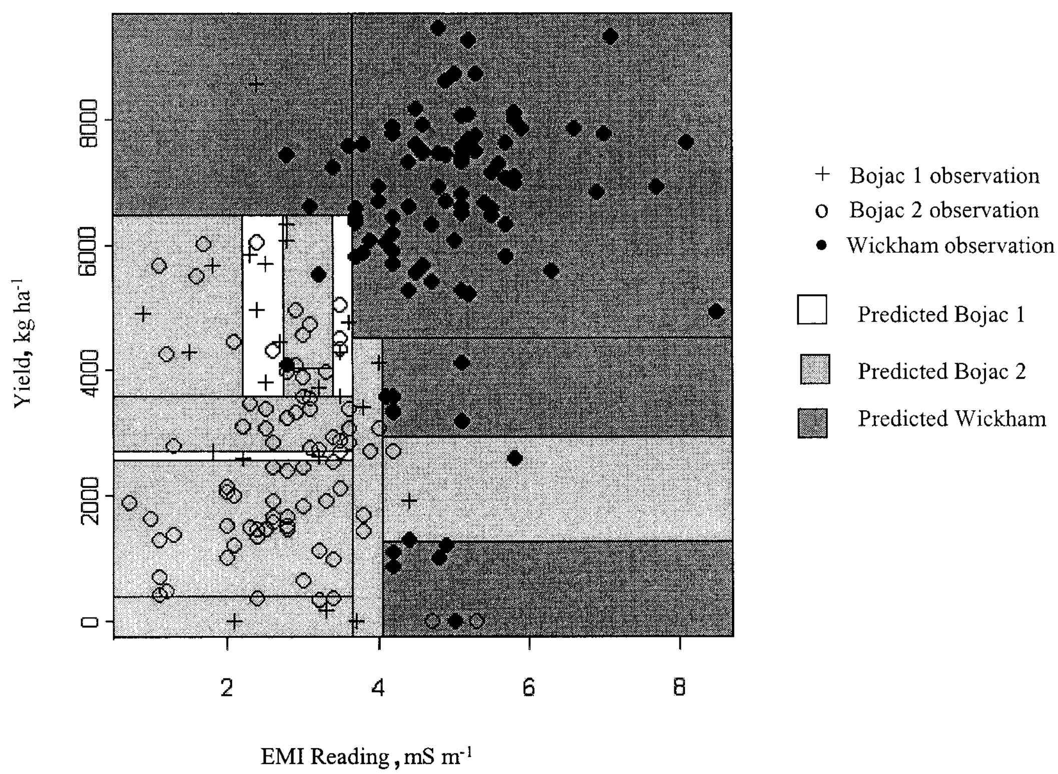

Fig. 6. Classification partition for Bojac 1, 2 versus Wickham soil types using apparent electromagnetic conductivity (EC_a) and 1999 no till full-season corn yields. The classification of each rectangle is determined by whichever soil type comprises the majority of observations.

metric flexible model that has been used, this result is quite remarkable. Note how the actual observations show a natural clustering into three groups. The unshaded region indicates the Bojac 1 soil type, which is characterized by low EC_a readings and moderate corn yields. The lightly shaded region indicates Bojac 2 soil, which is made up primarily of low EC_a readings and low corn crop yields. Finally, the Wickham soils are shown on the partition with the darker shading, and consist of high EC_a readings, high corn yields or both. The separation of soil types into these simple combinations of EC_a readings and crop yields was also observed in both the 1999 wheat and barley yields.

The 1999 corn crop classification has a similar correct classification rate, but the regions for separating the soils are not as easily characterized (Fig. 6). There are some combinations of EC_a readings and yields for the Bojac 1 and 2 soils, which are not easily distinguished. This type of messy summary from a classification tree is not uncommon and was also observed for the 1999 soybean data. However, the identification of the Wickham soil continues to be the combination of high EC_a readings, high crop yields, or both. The actual observations also show fewer clustering patterns than the 1998 data. For example, there seem to be high, medium, and low values of corn yields for the Bojac 1 soil type. When we examine the misclassification of the soil types in Tables 6 and 7 for 1998 and 1999 no-till full-season corn data, we see that the Wickham soil is most often correctly classified, while some values of the Bojac soils are not easily separated. Clearly, it is more difficult to distinguish between the Bojac 1 and 2 soils than to separate them from the Wickham soils, as shown by the varied misclassification rates in the different categories. There are many similarities in texture between the two Bojac soils (Table 1), which may explain their consistent EC_a values.

CONCLUSIONS

Soil type classification using electromagnetic induction with a statistical classification tree approach shows considerable promise for separating mid-Atlantic coastal plain soils into broad ranges of potential productivity.

Table 6. Classification rates for individual soil types using EC_a and 1998 no till full-season corn yields for Bojac 1 and 2 versus Wickham soil types.

True soil type	Number of observations	Predicted soil type		
		Bojac 1	Bojac 2	Wickham
		%		
Bojac 1	28	67.9	21.4	10.7
Bojac 2	46	6.3	89.1	4.3
Wickham	55	3.6	5.5	90.9

Table 7. Classification rates for individual soil types using apparent electric conductivity EC_a and 1999 corn yields for Bojac 1 and 2 versus Wickham soil types.

True soil type	Number of observations	Predicted soil type		
		Bojac 1	Bojac 2	Wickham
		%		
Bojac 1	24	45.8	50.0	4.2
Bojac 2	81	8.7	88.9	2.4
Wickham	92	0.0	4.3	95.7

For separating soil types with significant subsoil texture differences, such as Bojac and Wickham soils, the EC_a readings alone are able to correctly classify the soil type over 85% of the time. When combined with a crop yield located with a GPS device, the correct classification rate increases to over 90%. The EC_a readings and the crop yields are positively correlated, and high measurements of both EC_a and crop yields are associated with the Wickham soils, while lower measurements of both are associated with the Bojac soils. Depending on crop treatment, the rare combinations of high EC_a and low crop yield, or low EC_a and high crop yields are categorized differently.

Classifying soils into more precise soil types, such as Bojac 1, 2, and Wickham soils is more difficult. Correct soil classification rates using EC_a readings alone range from 62 to 81%, and increases to between 80 and 91% when combined with GPS crop yield information. Yield data generally improve the classification over EC_a data alone because crop yields tend to reflect soil moisture holding capacities for coastal plain soils.

In this mid-Atlantic coastal plain study, electromagnetic induction technology showed considerable promise as a tool for soil classification, and could be a cost-effective basis for development of variable rate fertilizer application strategies.

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